



RESEARCH ARTICLE

Pollution and the public: how information accessibility conditions the public's responsiveness to policy and outcomes

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Abstract

This article advances a theory that brings real-world outcomes into our current understanding of the dynamic relationship between public opinion and policy. It examines a vital public good – air pollution remediation in 319 American localities – and estimates a dynamic model of relationships among three key variables: public opinion, policy, and air pollution outcomes. The analysis focuses on both public opinion and air pollution outcomes as dependent variables. I find that public opinion reacts to changes in statewide policy and local air pollution, which suggests the public forms its opinions with whatever reliable information is most readily available. I also find that local public opinion's impact on local air pollution is substantively meaningful on timescales smaller than 5 years, indicating that the additional policy effort prompted by public opinion change is sufficient to yield tangible real-world outcomes even in the short term.

Key words: policy representation; air pollution; environmental policy; public opinion; state and local government

Introduction

To form coherent opinions about whether the government should increase (or decrease) its policy efforts to address an issue, the public needs information. The information must be somehow associated with policy for it to be useful for forming these opinions. It can be about policy itself – i.e. the decisions and actions of governmental actors. It can also be about policy's real-world outcomes, which can be used to evaluate whether current policy levels are sufficient to address a given issue. Worsening outcomes, for instance, may indicate that current policy efforts are inadequate.

The public regularly uses available policy information to update its opinions. Scholarship has shown that policy change has a robust statistical effect on the public's preferences in salient issue domains (Wlezien 1995; Jennings 2009), which

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reflects the public using information about policy itself.¹ The public's use of available outcomes information is not well understood, as studies have yielded seemingly contradictory results. Some have found outcomes' statistical effect on public opinion to be robust, which suggests that the public uses information about outcomes to update its opinions (Egan and Mullin 2012; Kim et al. 2020). Other studies have found this effect to be weak or insignificant (Borick and Rabe 2010; Soroka and Wlezien 2010, 107–124), indicating that the public often ignores available outcomes information. The unexplained inconsistency of these findings points to an important question: what determines whether the public uses available information to update its opinions?

I propose a model in which public opinion's responsiveness to information is conditioned by the information's accessibility – i.e. the level of effort private citizens must expend to obtain and understand it. I argue that the public updates its opinions primarily with whatever seemingly reliable information is most accessible.

To test this model, I examine a vital public good – air pollution remediation in 319 American localities from 2010 through 2018 – and estimate a dynamic model of relationships among three key variables: public opinion, policy, and air pollution outcomes.² The analysis focuses first on public opinion as the dependent variable (DV); I estimate the effects of policy and outcomes for which information is easily accessible to the public and compare them to the effects of policy and outcomes for which information is less accessible. My model predicts that public opinion will be more responsive to highly accessible information than to relatively inaccessible information. I then turn to analyzing outcomes as the DV and public opinion and policy as explanatory variables (EVs), which allows me to assess the real-world impact of the policy changes prompted by shifts in public opinion.

This study builds upon the “thermostatic” responsiveness literature by modelling outcomes' relationship with public opinion and policy. The thermostatic literature finds that public opinion and policy have a reciprocal relationship; policy change moves public opinion which then prompts more policy change, creating a process that feeds back on itself. The thermostatic literature does not include outcomes as part of this dynamic (Wlezien 1995; Wlezien 2004; Jennings 2009; Soroka and Wlezien 2010).

Accounting for outcomes is important because both policy and outcomes reflect large bodies of information the public can – and often does – use to update its opinions. While they are deeply connected, outcomes often cannot be reliably inferred from measures of policy itself, at least not with any degree of precision. The policy–outcomes relationship is inherently noisy because policy efforts interact with real-world conditions in complex ways. Thus, even carefully designed policies frequently yield unanticipated results (see Ranson et al. 2015; McDermott et al. 2019), and outcomes can vary without evident changes in policy (see Gulzar and Pasquale 2017).³

¹Studies have also established that citizens can recognize and accurately interpret available information about policy change (Neuner et al. 2019), and that exposure to policy information increases citizens' policy-specific knowledge and influences their attitudes (Druckman 2001; Barabas and Jerit 2009).

²The sample includes all metropolitan areas for which data are available.

³The inherent noisiness of the policy–outcomes relationship is compounded by the difficulty of systematically measuring policy implementation. Most of the policy measurements used in the literature are based on policy deliberations (e.g. committee hearings and roll call votes) or outputs (e.g. legislation and budgets), which are comparatively easy to measure. However, implementation is the aspect of the policy process that

By incorporating outcomes into the responsiveness dynamic, this study advances a more complete model of public opinion change. Identifying the conditions under which the public uses policy and outcomes information improves our understanding of how and why public opinion changes over time. Accounting for outcomes also makes it possible to assess the substantive significance of public opinion change – that is, the degree to which it affects outcomes.

Theory

Scholarship has shown that public opinion is often sensitive to changes in policy and outcomes. Of course, the public does not react to policy and outcomes changes *per se*. Rather, it reacts to information about policy and outcomes that indicates change (see Williams and Schoonvelde 2018). Logic dictates that information must be at least minimally accessible for the public to react to it, for citizens cannot update their opinions with information they cannot both obtain and understand.

This study's central argument is that the degree of information's accessibility – i.e. the amount of effort citizens must expend to obtain and understand it – is an important determinant of whether the public uses the information to update its opinions. This argument is based on the assumption that the public is boundedly rational, which implies that citizens become less inclined to use a given body of information as the difficulty of doing so increases (see Jones 2003). Hypotheses 1 and 2 follow from this line of reasoning:

H1: Public opinion is more responsive to policy changes about which information is easily accessible and less responsive to policy changes about which information is relatively inaccessible.

H2: Public opinion is more responsive to outcomes changes about which information is easily accessible and less responsive to outcomes changes about which information is relatively inaccessible.

Hypothesis 1 is supported by extant scholarship, which has shown that public opinion's sensitivity to policy change is lower when policy information is largely inaccessible (Williams and Schoonvelde 2018; Hiaeshutter-Rice et al. 2019; Neuner et al. 2019). Scholarly support for Hypothesis 2 is less straightforward because studies of outcomes' effect on public opinion have produced conflicting results. Nevertheless, when taken together, these seemingly contradictory findings are consistent with the second hypothesis. The studies that find strong effects measure outcomes that are highly visible and proximate to citizens' daily lives, such as the construction of local energy infrastructure and local school performance (Janvry et al. 2010; Stokes 2016). The studies that find weak or nonexistent effects measure outcomes that are abstract and distant from citizens' daily lives, like nationwide economic performance and state-wide temperature increases (Ansolabehere et al. 2014, Bergquist and Warsaw 2019). Given that information about visible nearby outcomes tends to

most directly produces outcomes, and implementation efforts can vary significantly without changes to policy outputs or the deliberations that precede them.

be more accessible to the public than information about abstract distant outcomes, these findings are consistent with Hypothesis 2.

The sign of policy change's effect on the public's preferences is usually negative. That is, when the government increases (decreases) its policy efforts to address an issue, the public's preference for further increases (decreases) goes down (Wlezien 1995, Soroka and Wlezien 2005; Jennings 2009; Soroka and Wlezien 2010; Wlezien and Soroka 2012; Pacheco 2013).⁴ The sign of outcomes' effect on preferences depends on whether an increase in outcomes is defined as an improvement or deterioration in real-world conditions. This study uses the latter definition, meaning that the term *outcomes* is synonymous with problem severity. When problem severity increases, the public's preference for the government to do more about it tends to increase as a result (see Oehl et al. 2017).

H3: When policy information is easily accessible, policy change's effect on the public's policy preferences has a negative sign.

H4: When outcomes information is easily accessible, outcomes change's effect on the public's policy preferences has a positive sign.

Measurement

This study's empirical strategy depends on objectively measuring policy and outcomes about which information is easily accessible, and policy and outcomes about which information is relatively inaccessible. To do this, I measure air pollution remediation policy and outcomes at the local and statewide levels in the United States (US).

Regarding air pollution outcomes, local information is more accessible than statewide information. The former is inherently accessible because it is directly observable in daily life. Indeed, it is accessible to the point of being unavoidable – citizens receive information about local air pollution with every breath they take. The information from direct observations is reasonably accurate and precise, as even small short-term increases in air pollution exposure increase physical discomfort (Rotko et al. 2002; Amundsen et al. 2008). Statewide outcomes information is less accessible because very few citizens directly observe air pollution across entire states in their daily lives. While there is certainly a relationship between statewide air pollution levels and the local air pollution citizens experience, the two are only loosely correlated. Air quality varies significantly over distances as short as a few tens of kilometers.

The air pollution information citizens can deliberately seek out is also more accessible for the local level than for the statewide level. The Air Quality Index (AQI) is the most ubiquitous measure of air pollution in contemporary American society.⁵ It is regularly reported in popular media, used by most cell phone apps that indicate air quality, and can be easily looked up with a simple

⁴There are cases in which policy change's effect on preferences is positive. The creation of an entirely new social service, for example, can increase the public's desire for the government to further expand the service. Such occurrences, however, are relatively rare and usually short-lived (e.g. Lü 2014).

⁵The AQI is a composite measure of multiple air pollutants.

internet search. The AQI is available for most cities in the US but not for entire states. Sufficiently motivated citizens can obtain statewide air pollution information, of course (e.g. the air pollution measures used in this study are open source), but doing so usually requires significant effort.⁶

Regarding policy, local information is generally less accessible than statewide information. Neither local nor statewide policy information is inherently accessible; policy efforts are not normally observable in daily life, and the policy information citizens can obtain directly from the government (e.g. regulatory enforcement records) often requires considerable time and expertise to interpret. The accessibility of policy information therefore depends heavily on the degree to which intermediaries obtain, interpret, and disseminate such information.⁷ Intermediaries are scarce at the local level (see Meyer 2009) and are relatively prominent at the state level, as is evidenced by public opinion's sensitivity to state-level policy changes and governmental performance (Lyons et al. 2013; Pacheco 2013).

Unit of analysis

The unit of analysis for this study is locality-year. The localities are metropolitan statistical areas (MSAs), which are socio-economic entities, not political jurisdictions. They are defined by the Office of Management and Budget as major urban centers plus the surrounding counties from which they draw their labor force.

MSAs are the appropriate unit because their average pollution levels reflect what the average person experiences on a daily basis at home and at work. Furthermore, because most air pollution at a given location is from nearby socio-economic activities, the policy efforts most relevant for influencing a person's pollution exposure are those carried out within the same MSA.

Public opinion

I measure public opinion with the Google Trends internet search index, which indicates the annual proportion of air pollution-related searches in each locality. For the primary models presented below, the search index values are for the following combination of terms: *smog* + *no2* + *air pollution* + *ozone* + *pm2.5* + *AQI*. In Appendix B in the Supplementary material, I show results that exclude the term *AQI* to demonstrate robustness.

Fundamentally, search indexes like Google Trends reflect an issue's *salience* – when people perceive an issue to be an urgent problem, they spend more time looking it up online (Reilly et al. 2012; Mellon 2013). *Salience* is distinct from *preferences*, which refer to how much the public wants the government to do about an issue. *Salience* and *preferences* are not necessarily correlated; there can simultaneously be both broad agreement that an issue is an urgent problem and sharply divergent views about how much the government should do about it.

⁶Understanding the information available at the statewide level (e.g. aerosol optical depth measurements) also tends to require a high degree of technical knowledge.

⁷An intermediary can be any person or organization with the time and expertise to perform these three functions. Common examples of intermediaries include political parties, interest groups, and journalists.

The air pollution issue domain is a special case in which salience and preferences closely correspond. In their 2017 study, Oehl, Schaffer, and Bernauer compare Google Trends data to survey measures of policy preferences. They establish that the public's attention to an issue and the degree to which it wants the government to do more about it are highly correlated in domains related to air pollution emissions. Thus, in the context of this study, the search index reflects both salience and preferences. Hereafter, I use the term *public concern* to refer to this special case of public opinion.

The public concern variable is based on Google Trends data for designated market areas (DMAs).⁸ DMAs are the smallest geographic unit for which Google Trends data are available nationwide. There are 210 DMAs, which cover the entire US. Most are centered on metropolitan hubs, meaning their boundaries tend to roughly correspond with those of large- and mid-sized MSAs. Ohio's Cleveland–Akron–Canton area, for instance, is both an MSA and a DMA. Many smaller MSAs straddle the boundaries between two or more DMAs. For these MSAs, public concern is calculated as the mean Google Trends value for the DMAs the MSA overlaps. Measurement error is almost certainly higher for the smaller MSAs that straddle multiple DMAs, which increases the noisiness of statistical estimates and biases them away from significance. Fortunately, the size of this measurement error appears to be modest; dropping smaller MSAs from the sample yields statistical estimates that are comparable to those shown in the analysis section.

Because DMAs cover the entire US, they include rural areas that are not part of any MSA. The Google Trends values for most MSAs therefore include internet traffic in adjacent rural areas. Due to their relatively small populations and low rates of internet connectivity, searches in rural areas are unlikely to meaningfully affect the Google Trends measure. This is especially true for searches related to air pollution, which tends to be more salient in urban areas. To the extent internet traffic in adjacent rural areas introduces measurement error, it should bias the analysis against finding significant relationships.

Policy

Policy is measured by aggregating all enforcement actions of the Clean Air Act (CAA) that take place in states and localities each year. The enforcement actions consist of ongoing federally reportable violations (FRVs), ongoing high-priority violations (HPVs), formal disciplinary actions (e.g. issuing fines), and informal disciplinary actions (e.g. issuing notices of noncompliance). These actions are undertaken by authorities at all levels of the political system.⁹

I aggregate all actions that take place within the states and localities, regardless of which levels of the political system execute them. This is appropriate because the policy efforts relevant to air pollution levels in an area are not specific to any one level of government.

⁸The Google Trends values for each year are weighted by the national trend for the search terms to make the values comparable over time.

⁹The enforcement actions are recorded by the Environmental Protection Agency (<https://echo.epa.gov>).

Outcomes

I measure ground-level air pollution outcomes with two ubiquitous pollutants – nitrogen dioxide (NO₂) and fine particulate matter (PM_{2.5}) – which are indicative of a locality's overall air pollution level. NO₂ and PM_{2.5} typically have correlations of over 0.7 with other major air pollutants, including coarse particulate matter (PM₁₀), carbon monoxide (CO), and sulfur dioxide (SO₂) (Guo et al. 2017).¹⁰

NO₂ is the primary pollution measure for this analysis because it closely reflects local emissions, while PM_{2.5} is more sensitive to emissions region-wide. NO₂ has a short lifespan, which is comparable to other non-particulate air pollutants. It persists in the lower atmosphere for around one to two days before breaking down, so most NO₂ does not travel beyond the local area of its emission source. PM_{2.5}, on the other hand, is an exceptionally long-lived air pollutant. It persists for days or weeks and can travel many hundreds of kilometers before falling out of the lower atmosphere (Jeong et al. 2017).

I leverage the different lifespans of these two pollutants in the empirical analysis. Comparing them makes it possible to infer the degree to which pollution changes are driven by local factors as opposed to regional or national influences.

NO₂ and PM_{2.5} concentrations are calculated with daily satellite overpass data. The NO₂ data are from the DOMINO (version 2) and TM4NO2A (version 2.3) datasets provided by the European Space Agency (ESA). The PM_{2.5} data are from the Global Annual PM_{2.5} Grids provided by NASA's Socioeconomic Data and Applications Center. I discuss the details of how I process the data in Appendix F in the Supplementary material.

Measurement validity

While these measures are somewhat unconventional in political science, they are nevertheless exceptionally well suited for this study because they are direct, independent measures of the concepts of interest. The Google Trends measure reflects actual human behavior associated with concern (Swearingen and Ripberger 2014). This sidesteps a major limitation of survey responses, which do not necessarily reflect people's actual perceptions (see Bullock et al. 2015). Google Trends also has higher spatial and temporal resolution than is feasible with surveys.

The CAA enforcement measure is a better measure of policy variation than more conventional measures, as implementation efforts vary considerably even without statutory changes (Wood and Waterman 1993).¹¹

NO₂ and PM_{2.5} concentrations are objective measurements of policy outcomes. They are validated by ESA and NASA and are entirely independent of the other concepts of interest. They do not depend on ground sensors, the distribution of which is influenced by pollution severity, policy efforts, and public opinion.

¹⁰The correlation between NO₂ and PM_{2.5} in my sample is 0.7.

¹¹CAA enforcement actions have been used extensively in studies of regulatory enforcement (see Konisky and Woods 2010).

Control variables

Partisanship

Partisanship can affect citizens' environmental concerns and how they process information. Those affiliated with the Democratic Party are more inclined to becoming concerned with environmental issues when they observe deteriorating conditions (Egan and Mullin 2012). I therefore control for local partisanship in models with public concern as the DV. I measure partisanship as each locality's average Democratic presidential candidate vote share for the time period of this study.

Economic output

Economic output must be controlled for in models with air pollution as the DV. This is because nearby economic activity is the primary driver of local air pollution in general and non-particulate pollutants like NO₂ in particular (Chan and Yao 2008; Jiang et al. 2014; Jeong et al. 2017). Local economic output (i.e. gross regional product – GRP) values are from the Bureau of Economic Analysis and inflation adjusted.

Pollution spillover

Spillover is not a serious concern for NO₂ because it breaks down quickly in the atmosphere. The models presented below therefore simply ignore it. As a robustness check, I account for statewide NO₂ levels and find consistent results (see Appendix D in the Supplementary material).¹² Nonlocal emissions are a major contributor to local PM_{2.5}. This makes PM_{2.5} levels less sensitive to local events, but there is no reason that spillover would bias measurement of PM_{2.5} itself or its estimated relationships with other variables of interest.

Unmeasured variables

Unmeasured determinants of public concern and air pollution

There are, of course, variables beyond those listed above that influence public concern and air pollution. Most notably, demographic characteristics like race and education are associated with environmental attitudes (Egan and Mullin 2012), and geography and climate are major determinants of air pollution levels (Chan and Yao 2008; Jiang et al. 2014; Jeong et al. 2017).

I use lagged dependent variables (LDVs) to control for unmeasured factors like these. An LDV reflects all determinants of the DV's value in the previous year, so it controls for any unmeasured EVs that do not change substantially from 1 year to the next. As an additional precaution, I use state fixed effects to control for any unmeasured regional factors that are not accounted for by the locality-specific LDVs.

¹²Lagged spatial autoregression (SAR) models, which treat NO₂ spillover as an endogenous phenomenon between each locality and its neighbors, also yield consistent results.

Unmeasured policy

CAA enforcement actions are a good measure of policy efforts that explicitly target air pollution. However, many of the policy tools state and local authorities use to address air pollution do not explicitly target emissions. Examples of these tools include zoning rules, building permits, and other regulations and incentives that influence the locations of pollution sources.

Information about non-explicit policy is unlikely to be a significant factor driving public concern. Due to its obscure nature, the public almost certainly uses far less information about non-explicit policy than about explicit policy and visible outcomes.

Although the efforts themselves are difficult to observe, the aggregate impact of non-explicit policy on air pollution is significant (Monogan et al. 2016). Studies that infer non-explicit policy variation through air pollution outcomes suggest that non-explicit policy efforts are highly responsive to local public opinion (Pargal et al. 1997; Pinault et al. 2016; Huang et al. 2018).

Model specification

The basic framework for the statistical models is a system of three equations in which each variable of interest is a function of the other two. The DVs of greatest interest are public concern and air pollution. As stated above, the models include LDVs to account for unmeasured factors that do not change substantially from 1 year to the next. By including LDVs, the coefficients for the other EVs reflect the extent to which they explain each DV's change from the previous year. For this reason, most of the EVs are expressed as their change since the previous year.

Naive models

The system of relationships can be expressed as a trio of independent linear models and estimated with ordinary least squares (OLS). In Equations 1, 2, and 3, *Search* is the Google Trends search index that measures public concern. *Enforce* is CAA enforcement actions, which measure policy. *NO2* is the concentration of the nitrogen dioxide air pollutant, which measures outcomes. Models that measure outcomes with $PM_{2.5}$ replace each instance of NO_2 with $PM_{2.5}$ and are otherwise identical (see Appendix E in the Supplementary material). *GRP* is gross regional product, which refers to local economic output. The Δ 's signify year-on-year change. The α 's are intercepts, the β 's are coefficient estimates, the e 's are error terms, and the $\hat{\gamma}$'s are vectors of control variables. The i and t subscripts refer to the locality and year of each observation, respectively. Note that each coefficient, vector, intercept, and error term has one or two subscript numbers. These indicate that the values are unique (e.g. the first β in Equation 1 is different from the other β 's in the same equation and the first β 's in Equations 2 and 3):

$$\begin{aligned} Search_{i,t} = & \alpha_{1,0} + \beta_{1,1}Search_{i,t-1} + \beta_{1,2}\Delta NO2_{i,t} + \beta_{1,3}\Delta Enforce_{i,t} \\ & + \beta_{1,4}\Delta Statewide NO2_{i,t} + \beta_{1,5}\Delta Statewide Enforce_{i,t} + \hat{\gamma}_{1,i} + e_{1,i,t} \end{aligned} \quad (1)$$

$$\begin{aligned} Enforce_{i,t} = & \alpha_{2,0} + \beta_{2,1}Enforce_{i,t-1} + \beta_{2,2}\Delta Search_{i,t-1} + \beta_{2,3}\Delta NO2_{i,t-1} \\ & + \beta_{2,4}\Delta Statewide Search_{i,t-1} + \beta_{2,5}\Delta Statewide NO2_{i,t-1} + \hat{\gamma}_{2,i} + e_{2,i,t} \end{aligned} \quad (2)$$

$$NO_{2,i,t} = \alpha_{3,0} + \beta_{3,1}NO_{2,i,t-1} + \beta_{3,2}\Delta GRP_{i,t} + \beta_{3,3}\Delta Search_{i,t-1} + \beta_{3,4}\Delta Enforce_{i,t-1} + \beta_{3,5}\Delta Statewide\ Search_{i,t-1} + \beta_{3,6}\Delta Statewide\ Enforce_{i,t-1} + \hat{\gamma}_{3,i} + e_{3,i,t} \quad (3)$$

Structural equation models

The equations above are estimated as three independent models. If the theory underlying these equations is correct, however, the relationships they depict form a dynamic system in which some combination of policy and outcomes affects public concern, which then goes on to affect policy and outcomes. The naive estimates shown in Figure 1 (and Table 1) in the next section suggest a robust dynamic between the search index and NO_2 – the search index has a strong effect on NO_2 , and NO_2 has a strong effect on the search index. If this pair of relationships does indeed reflect a process feeding back on itself, the search index and NO_2 should have correlated errors and biased estimates. The magnitude of bias from feedback is typically quite modest and can generally be ignored during estimation (see Hermida 2015). Nevertheless, the presence (or absence) of this bias provides additional evidence for (or against) the existence of a dynamic process.

If the theorized dynamic exists, the naive estimates for NO_2 's effect on the search index and the search index's effect on NO_2 should be biased towards zero because the two relationships have opposite signs (i.e. the search index's effect on NO_2 has the opposite sign of NO_2 's effect on the search index).¹³ This bias is introduced by unmeasured shocks to public concern and air pollution that persist over time. A shock that increases public concern – new high-profile medical research on pollution's health consequences, for instance – would cause NO_2 to decrease the following year via responsive policy. If the shock dissipated quickly, it would be like any other source of random error; it would inflate the unexplained variation of the search index but would not introduce bias. If, however, the shock's effect on concern persisted for multiple years, the search index would remain high even as contemporary NO_2 levels continued to decrease. This would bias pollution severity's estimated effect on the search index in the negative direction (i.e. towards zero). Similarly, a shock to air pollution that persisted would bias the search index's estimated effect on it in the positive direction. If an exogenous event like natural gas prices falling relative to coal caused a multi-year decrease in pollution levels, those lower levels would decrease public concern as measured by the search index. If, as the search index decreased, the shock continued to reduce pollution levels, the search index's estimated effect on NO_2 would be biased in the positive direction (i.e. towards zero).

I use structural equation models (SEMs) to test for the error correlation and bias the theorized dynamic should create. An SEM can specify error correlation between specific variables, which is accounted for when the model is estimated. I compare the performance of an SEM that specifies error correlation between the search index and NO_2 to an otherwise identical SEM that does not. If the dynamic exists, then the effects of *Search* and *NO2* on one another should be (modestly) larger – and the relative fit better – for the SEM that specifies the expected error correlation:

¹³For dynamics in which both relationships have the same sign, the estimates would be biased away from zero.

$$\begin{aligned} Search_{i,t-1} = & \alpha_{4,0} + \beta_{4,1}Search_{i,t-2} + \beta_{4,2}\Delta NO_{2,i,t-1} + \beta_{4,3}NO_{2,i,t-1} \\ & + \beta_{4,4}\Delta Enforce_{i,t-1} + \beta_{4,5}Enforce_{i,t-1} + \hat{\gamma}_{4,i} + e_{4,i,t-1} \end{aligned} \quad (4)$$

$$\begin{aligned} Enforce_{i,t} = & \alpha_{5,0} + \beta_{5,1}Enforce_{i,t-1} + \beta_{5,2}Search_{i,t-1} \\ & + \beta_{5,3}\Delta NO_{2,i,t-1} + \beta_{5,4}NO_{2,i,t-1} + \hat{\gamma}_{5,i} + e_{5,i,t} \end{aligned} \quad (5)$$

$$\begin{aligned} NO_{2,i,t} = & \alpha_{6,0} + \beta_{6,1}NO_{2,i,t-1} + \beta_{6,2}\Delta GRP_{i,t} + \beta_{6,3}Search_{i,t-1} \\ & + \beta_{6,4}Enforce_{i,t-1} + \beta_{6,5}\Delta Enforce_{i,t-1} + \hat{\gamma}_{6,i} + e_{6,i,t} \end{aligned} \quad (6)$$

Note that *Search*, *Enforce*, and *NO₂* are included as EVs in the SEM equations, and that the *Search* DV is lagged by 1 year (with its EVs lagged accordingly) so that it matches the lag of the *Search* EV in the *NO₂* equation. This is necessary for estimating error correlation between the search index and *NO₂*.

Analysis

Figure 1 summarizes the key statistical relationships shown in Table 1. The search index and *NO₂* (and *PM_{2.5}* in Appendix E in the Supplementary material) measure public concern and air pollution outcomes, respectively. The enforcement variable, *Enforce*, refers to CAA enforcement actions, which reflect policy effort to mitigate air pollution. Variables that include the word *statewide* refer to values for the state in which the locality is located.¹⁴ The unit of analysis is locality-year. The models include all US localities for which data are available – 319 MSAs from 2010 through 2018.

Public opinion's responsiveness to information

The four variables' effects on the search index shown in Figure 1(a) and (b) reflect the degree to which the public uses information about each to update its concerns. Local *NO₂* and statewide enforcement's highly significant effects indicate that the public uses information about local air pollution outcomes and statewide policy. Local *NO₂*'s positive sign shows that the public becomes more concerned with air pollution as the problem becomes worse in daily life. Statewide enforcement's negative sign shows that the public becomes less concerned with air pollution as governmental authorities do more to mitigate the problem statewide. The magnitudes of local *NO₂* and statewide policy's effects are substantively meaningful, with local *NO₂*'s effect being the larger of the two. A one standard deviation increase of local *NO₂* would increase the search index by 0.13 standard deviations, a 9% change for the average observation. A one standard deviation increase of statewide enforcement would decrease the search index by 0.10 standard deviations, a 7% change for the average observation.¹⁵

¹⁴Localities that straddle state boundaries are assigned to the state that contains the largest amount of its land area.

¹⁵Local *NO₂* having the larger of the two dominant effects is additional evidence for my central argument. Because it is directly observed in daily life, local air pollution information is almost certainly more accessible than statewide policy information. If this is indeed the case, a larger effect from local *NO₂* on the search index is what we should see if the public is more responsive to information that is more accessible.

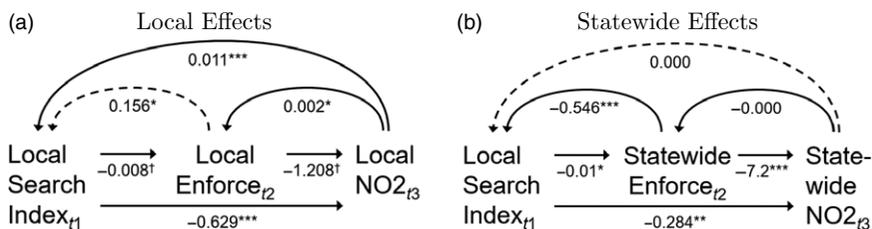


Figure 1. Results summary

Note: The arrows represent causal relationships. The dashed arrows indicate effects that are predicted to be weak relative to the other effects on the search index. The coefficients correspond to those of Model 3 in Tables 1 and C.1 in the Supplementary material. [†] $p < 0.1$; ^{*} $p < 0.05$; ^{**} $p < 0.01$; ^{***} $p < 0.001$.

Local enforcement and statewide NO₂'s effects on the search index are statistically and substantively weak, which suggests the public uses relatively little information about local policy and statewide outcomes to update its concerns. Statistically, local enforcement's effect straddles the conventional significance threshold; its p-value is slightly below the 0.05 threshold in the model as shown in Figure 1 ($p = 0.04$) and above it in the alternate model as shown in Table 1 ($p = 0.37$). Substantively, a one standard deviation increase in local enforcement would increase the search index by 0.03 standard deviations, a 2% change for the average observation. Statewide NO₂'s effect on the search index is practically nonexistent; its magnitude is negligible and is nowhere near statistical significance ($p > 0.9$).

The relative sizes of these four effects are consistent with my central argument. While all the policy and outcomes information measured in this study is available to anyone who wants it, public concern is consistently more responsive to the information that is more readily accessible. This suggests that the public's responsiveness to information is conditioned by the information's accessibility. There are no clear alternative explanations that can account for the dominant effects of both local outcomes and statewide policy on public concern. Together, these effects rule out the possibility that the public's use of available information is driven by a strong preference for policy information over outcomes information (or vice versa), or local information over statewide information (or vice versa).

Policy outcomes' responsiveness to public opinion

The search index's effect on air pollution reflects the outcomes of policy prompted by public concern. It is possible to infer policy outcomes' responsiveness to the public with this relationship because policy is the only mechanism through which public sentiment can significantly affect air pollution within the time span of this analysis. Popular concern can prompt individual-level behaviors that meaningfully affect air pollution without governmental action, but only on timescales dramatically shorter or longer than this analysis. For example, while severe smog often leads people to delay travel plans for days or weeks (Barwick et al. 2019), such behavioral changes have no net impact on pollution emissions over the course of an entire year (Welch

Table 1. Regressions with NO₂

(A)			
	(1)	(2)	(3)
<i>DV : Search_t</i>			
Search _{t-1}	0.559*** (0.015)	0.550*** (0.014)	0.555*** (0.015)
ΔNO _{2t}	0.011*** (0.002)		0.011*** (0.003)
ΔEnforce _t	0.061 (0.068)		0.156* (0.072)
ΔNO _{2t} (statewide)		0.011*** (0.003)	0.000 (0.004)
ΔEnforce _t (statewide)		-0.423** (0.137)	-0.546*** (0.147)
<i>F</i> Statistic	431.14	437.17	417.24
Resid. Std. Error	3.43	3.41	3.43
R ²	0.89	0.89	0.89
<i>N</i>	2,818	2,889	2,818
(B)			
	(1)	(2)	(3)
<i>DV : Enforce_t</i>			
Enforce _{t-1}	1.028*** (0.005)	1.027*** (0.005)	1.028*** (0.005)
ΔSearch _{t-1}	-0.006 (0.004)		-0.008† (0.004)
ΔNO _{2t-1}	0.000 (0.001)		0.002* (0.001)
ΔSearch _{t-1} (statewide)		0.003 (0.005)	0.006 (0.006)
ΔNO _{2t-1} (statewide)		-0.001 (0.001)	-0.003** (0.001)
<i>F</i> Statistic	1102.81	1115.76	1063.42
Resid. Std. Error	0.97	0.96	0.97
R ²	0.95	0.95	0.95
<i>N</i>	3,130	3,230	3,130
(C)			
	(1)	(2)	(3)
<i>DV : NO_{2t}</i>			
NO _{2t-1}	0.868*** (0.010)	0.866*** (0.010)	0.865*** (0.010)
ΔGRP _t	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
ΔSearch _{t-1}	-0.638*** (0.138)		-0.629*** (0.142)
ΔEnforce _{t-1}	-2.433*** (0.607)		-1.208† (0.643)
ΔSearch _{t-1} (statewide)		-0.330† (0.177)	-0.129 (0.183)
ΔEnforce _{t-1} (statewide)		-7.895*** (1.235)	-7.200*** (1.311)
<i>F</i> Statistic	656.44	658.39	639.45
Resid. Std. Error	31.37	31.32	31.20
R ²	0.93	0.93	0.93
<i>N</i>	2,818	2,818	2,818

Note: All models include state fixed effects. The models in subtable *a* control for each locality's Democratic vote share in presidential elections. †*p*0.1; **p*0.05; ***p*0.01; ****p*0.001.

et al. 2005). Without policy intervention, public concern only leads to durable changes in individual-level pollution-generating activities (e.g. driving habits) on timescales of a decade or longer (see Tribby et al. 2013).¹⁶

It is necessary to infer responsiveness from the search index's "direct" effect on air pollution because the enforcement variable is only a partial measure of total policy effort in a given geographic area. As discussed above, CAA enforcement actions do not reflect non-explicit policy efforts like the strategic use of zoning rules and building permits to influence the placement of emission sources. There is ample evidence that state and local officials regularly use non-explicit policy tools to address air pollution problems in their jurisdictions, and that their use of these policy tools is sensitive to public opinion (Pargal et al. 1997; Monogan et al. 2016; Pinault et al. 2016; Huang et al. 2018).

The search index's estimated effect on air pollution strongly suggests that unmeasured policy is responsive to local public concern. If unmeasured policy efforts are prompted by local shifts in public concern, a robust negative effect of the search index on local air pollution is what we should see. Local-level policy responsiveness is further evidenced by the relative sizes of the search index's effects on NO₂ and PM_{2.5}, as searches' negative effect on NO₂ is significantly stronger than it is on PM_{2.5} (see Appendix E in the Supplementary material). Given that a higher proportion of the former is from local sources, the search index's larger effect on NO₂ implies the phenomenon that accounts for these effects is, to a significant degree, local.

The relative sizes of the effects on NO₂ and PM_{2.5} are also evidence against a major unmeasured exogenous event causing a spurious relationship between searches and air pollution. If, for instance, the relationship were due to a dramatic environmental catastrophe that shocked government officials into action and drew public attention nationwide, the search index's estimated effect on NO₂ would likely be smaller (or, at the very least, not significantly bigger) than its effect on PM_{2.5}.

The weakness of the search index's effect on the enforcement variable indicates that measured policy is not immediately responsive to local public concern. If it were, the search index's effect would be significantly positive. CAA enforcement actions are carried out by specialized regulatory entities, which tend to be less sensitive to public concern – and more sensitive to objective problem severity – than other governmental bodies (Mullin 2008). Thus, it is unsurprising that measured policy is not immediately responsive to public concern. That said, this analysis only assesses policy's responsiveness to year-on-year changes in public concern; it does not rule out the possibility that CAA enforcement actions are responsive to public concern changes on larger timescales.

Magnitude of policy outcomes' responsiveness

How substantively meaningful is policy outcomes' responsiveness to public concern? Based on Table 1's Model 3 estimates, a one standard deviation increase in the search index would reduce local NO₂ by 2.8 units the following year, which

¹⁶Environmental activism, which is driven by public concern, focuses primarily on pressuring various governing authorities to take some form of policy action (See Appendix G in Supplementary material).

is a 1.1% change for the average observation.¹⁷ 2.8 units of NO₂ roughly correspond to 1 µg/m³.¹⁸ The visibility in daily life of a change like this would depend on how evenly distributed it is over the course of a year, as a more even distribution would be less obvious. Assuming a perfectly even distribution and no access to technology (e.g. AQI indexes), annual changes of this size would become perceptible within around 5 years, as citizens' self-reported levels of discomfort have been found to shift significantly in response to NO₂ changes as small as 5 µg/m³ (Amundsen et al. 2008). Under realistic conditions, these changes would likely become apparent to the public much sooner. The effect size suggests near-term impacts on public health. Annual changes of this magnitude would have a small but significant impact on health outcomes within several years. Over longer periods, the health impacts would be profound (see Jacquemin et al. 2009).

A modest 1-year effect that becomes substantial over several years is consistent with what one would expect given the non-explicit nature of the policy efforts that appear to be responding to local public concern. Non-explicit policy efforts like the strategic use of zoning rules and building permits generally cannot force the immediate relocation of emissions sources (e.g. pollution-intensive industries and coal-fired power plants), but beyond the very short term, they can play a major role in retaining or pushing out existing pollution emitters and attracting or repelling new ones to an area.

Alternate explanations for the concern – outcomes relationship

The search index's robust negative effect on air pollution the following year is consistent with responsive policy yielding substantively meaningful outcomes. There are, however, competing explanations for this relationship that must be addressed. The most plausible of these is the following:

Policy reacting directly to air pollution severity. In this scenario, public concern and policy would correlate because they would be responding to the same signal, and – assuming the government's efforts were effective – searches would be negatively associated with air pollution the following year despite the absence of a causal link. The relationship between enforcement and air pollution accounts for this possibility. Local NO₂'s positive effect on enforcement suggests that measured policy is indeed sensitive to air pollution severity. However, if authorities were responding almost exclusively to air pollution itself and not public concern, enforcement's effect on NO₂ (and PM_{2.5}) should wipe out – or at least substantially reduce – the search index's estimated effect. What we actually see is that the search index

¹⁷The impact on PM_{2.5} would be 0.1 µg/m³, which is a 1.5% change for the average observation.

¹⁸NO₂'s unit of measurement is 10¹⁵ molecules/cm² of the tropospheric column, which does not convert cleanly into mass per unit of volume at the bottom of the column. The value of around 1 µg/m³ can be derived a couple different ways. One is to simply scale the satellite measurements based on values from ground-based sensors (376 µg/m³, or 200 ppb, is a fairly typical high NO₂ value for an urban area; high values in my dataset are around 1,000 * 10¹⁵ molecules/cm²). The other method is to calculate the mass of the NO₂ molecules in the tropospheric column and assume that most of the NO₂ molecules are low in the column where most other air molecules are concentrated. Both approaches yield estimates in the same general ballpark.

remains highly significant even with enforcement included as an EV for air pollution.¹⁹

The remaining possible explanations for the search index's estimated effect on air pollution are highly improbable. These explanations include:

Anomalous weather and reversion to the mean. In principle, anomalous weather increasing (or decreasing) a locality's air pollution for 1 year and returning to the mean the next year could create the search index's apparent effect on NO₂ (and PM_{2.5}). To do so, however, the anomalies would need to regularly affect local air pollution averaged over exactly one calendar year without being offset by other anomalies. Any weather anomaly longer than 1 year is an exogenous shock that persists over time. As discussed in the previous section, such shocks bias relationships towards zero and can be accounted for with SEMs (see below). Given that major weather anomalies often persist for multiple years (e.g. drought conditions), the net impact of anomalous weather is likely to bias the coefficient estimates *against* significance.

Other unmeasured variables. It is, of course, impossible to definitively prove there are no other factors causing a spurious relationship between the search index and air pollution, but the possibility is extremely remote. There are no apparent alternative explanations for this relationship that have not already been addressed, and the models explain around 93% of NO₂'s variation (and 73% for PM_{2.5}). These high R² values are due mostly to the LDVs, which account for key pollution determinants like infrastructure, economic composition, and geography that do not change significantly from 1 year to the next. Explaining nearly all of the pollutants' variation is further evidence that the models are not missing any important variables that could potentially bias the results and cause spurious correlations.

Further evidence of a dynamic process

In Table 2, the second model is an SEM that specifies error correlation between the search index and NO₂. The first model is an SEM that assumes the two variables are independent but is otherwise identical to Model 2. As discussed previously, any error correlation from the theorized dynamic should bias the relationships of interest towards zero. Thus – if the dynamic exists – ignoring it should lead to smaller estimates for Δ NO₂'s effect on the search index and the search index's effect on NO₂. This is exactly what we see. Moreover, Model 2's smaller AIC and SABIC values indicate that it has better overall fit than Model 1.²⁰

¹⁹Because CAA enforcement actions are more sensitive to objective problem severity than most other forms of policy, the *Enforce* variable should adequately account for all policy efforts directly prompted by air pollution.

²⁰The sample for the SEMs in Table 2 includes micropolitan areas. Excluding these areas does not meaningfully change the results. The SEMs also cover a different time span than the models shown in Table 1 (2007–2016 as opposed to 2010–2018). Changing the time span yields results that are broadly similar to those shown here but dramatically more sensitive to the inclusion of state and year fixed effects.

Table 2. SEM results

	(1)	(2)
<i>DV : Search_{t-1}</i>		
Search _{t-2}	0.833*** (0.008)	0.833*** (0.008)
Δ NO2 _{t-1}	0.004 (0.003)	0.008** (0.003)
NO2 _{t-1}	0.000 (0.001)	0.000 (0.001)
Δ Enforce _{t-1}	0.093 (0.108)	0.081 (0.108)
Enforce _{t-1}	0.066* (0.031)	0.069* (0.031)
<i>DV : NO2_t</i>		
NO2 _{t-1}	0.803*** (0.006)	0.804*** (0.006)
Δ GRP _t	0.009*** (0.002)	0.009*** (0.002)
Search _{t-1}	-0.140** (0.053)	-0.292*** (0.074)
Δ Enforce _{t-1}	-2.325*** (0.561)	-2.280*** (0.561)
Enforce _{t-1}	1.137*** (0.174)	1.150*** (0.174)
Feedback	No	Yes
Akaike (AIC)	86,540	86,534
Adj. BIC (SABIC)	86,786	86,783
R ² (Equation 1)	0.72	0.72
R ² (Equation 2)	0.94	0.94
R ² (Equation 3)	0.93	0.93

Note: $N = 4,679$. Estimator: ML. The search equation has year fixed effects. The NO2 equation has state fixed effects. Estimated using "lavaan" v0.6-2 in R Open 3.5.1. † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Discussion

This study builds upon the thermostatic responsiveness literature by incorporating real-world outcomes into a dynamic model with public opinion and policy. A key supposition of this model is that the public's responsiveness to information is conditioned by the information's accessibility. That is, the public tends to update its opinions primarily with whatever relevant information is easiest to obtain and understand. The empirical analysis finds strong evidence in support of this model. It shows that the relationships between public opinion, policy, and outcomes are consistent with the model's theoretical expectations and rules out plausible alternative explanations for the statistical estimates. It also finds modest error correlation between public opinion and outcomes, which is further evidence that the variables feed back on one another.

By identifying the conditioning effect of information accessibility, this study provides a coherent theoretical explanation for why extant scholarship has found outcomes and policy's effects on public opinion to be so inconsistent. More broadly, these findings offer deeper insight into how and why public opinion changes. The public's preference for more (or less) policy is the difference between two

factors: the actual level of policy and the desired level of policy (Soroka and Wlezien 2010, 22–26). While the thermostatic literature accounts for changes in the former, changes in the latter have so far been difficult to measure and study. The robust effect of air pollution on public concern in this analysis is an indication that the public's desired level of policy is sensitive changes in outcomes.

Supplementary material. To view supplementary material for this article, please visit <https://doi.org/10.1017/S0143814X22000241>

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